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Supply Chain Network Robustness Against Disruptions: Topological Analysis, Measurement, and Optimization

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Keywords
supply chain network topology, robustness, disruption, decision support, simulation, optimization.

Disciplines
Business and Corporate Communications | Entrepreneurial and Small Business Operations | Operations and Supply Chain Management | Organizational Behavior and Theory | Sales and Merchandising

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1. Introduction

The management of disruptions in modern supply chain networks is a timely and relevant topic for both managers and researchers alike. A disruption in a supply chain is an unplanned and unanticipated event that disrupts the normal flow of material [14]. Supply chains are inherently vulnerable to disruptions because they are interconnected, global, and volatile [4, 20, 47, 58]. A disruption may initially affect or disable a few entities in the system, but its cascading effects may propagate to many others, disrupting an entire system [24, 25, 42, 43]. Prior research has noted that the cascading effects of a disruption are difficult to understand in real world settings [20]. Disruptions may impede the flow of people, goods, information, and funds with serious consequences, such as lost market share, increased cost, or even company failure [9]. However, disruptions do not always end in dire consequences [56-58]. The outcome can be positively influenced by the robustness of the supply chain. To increase robustness, it is appropriate to design supply chain networks to be adaptable to different disruption scenarios (i.e., different disruption types and their effects) [20, 27, 28] and to have the ability to reconfigure or restructure the network and redistributes flows in the face of changing conditions [5, 24]. By considering multiple alternative networks, robustness can be enhanced by analyzing the effects of possible disruptions before they occur in different network configurations [5] providing valuable network robustness insight [22, 26] into supply chain performance [60].

Previous research has demonstrated the efficacy of a topological approach to rewiring networks to enhance robustness [63, 64]. Specifically, network robustness has been evaluated using various topologies [53], and this work was extended with a new robustness metric [64], and a new topological design approach to supply chain networks [63]. One of the noted weaknesses in previous work in network robustness in the face of supply chain disruptions is the absence of network optimization techniques in robustness analysis [63]. In this paper, we extend prior research by developing a decision support approach that will allow supply chain managers to evaluate the robustness of different supply chain network designs using both a topological approach and an optimization approach [46, 53, 63]. In fact, there have been recent calls for supply chain managers and researchers alike to better understand the structure of the supply chain to determine the ability to adapt and recover from supply chain disruptions [24, 54].

In the context of this research, topology is the relative spatial placement of nodes and their connections or links specifically within the supply chain network (see [62] for a description and discussion of network topologies). Here, we adopt the topological perspective and propose a framework for robustness evaluation, including metrics for robustness and analysis using simulation, graph analysis, and optimization. The decision support system (DSS) not only simulates various types of disruptions and evaluates their impacts, but also allows users to consider "what-if" scenarios by modifying the structure through the rewiring of the supply chain network [37]. The DSS can configure and rewire a supply chain network using models supported by the system. Meanwhile, if network construction and rewiring models provided by the DSS are insufficient, a user can also provide different supply chain network topologies for evaluation. In doing so, managers can evaluate different topological designs for robustness against disruptions. In a supply network context, the relationship between the network's topology and robustness in the presence of targeted and random attacks has been investigated using multi-agent model simulation, but the researchers did not consider rewiring nodes nor identifying nodes that would be most appropriate for fortification [37]. Therefore, our DSS incorporates both operational and topological metrics into a decision support tool to enable different ways to evaluate supply network robustness using context of transshipments and logistics in a supply chain.

This research contributes in two ways: First, through simulation, the DSS allows users to evaluate the before and after performance of a supply chain network given various types of disruptions, so that the network's robustness against these disruptions can be analyzed. These disruptions may be random or targeted to study the impact of disrupting a particular node in varying topological models. This analysis will aid in identifying supply chain nodes that should be fortified. Second, this research provides a combination of topological metrics for supply chain networks that are relatively quick to calculate yet can still accurately capture the performance of the network against disruptions as well as network optimization based on network topology. In doing so, this approach can provide both topological metrics (through network analysis) and operational metrics (through optimization). Topological metrics can accurately approximate the operational metrics, yet the former is much faster to calculate than the latter, and thus enable quick robustness evaluation of a large number of network designs or rewiring schemes. Therefore, from a decision analysis perspective, topological metrics are quick to derive reasonable solutions to network rewiring in the face of disruptions. The incorporation of both the topology analyzer and the optimization solver allows supply chains robustness to be examined.

Therefore, the purpose of this study is not to derive an optimal design of a network, but show that topological metrics perform quick and satisfactory evaluations of different designs. At the same time, the high similarity between topological metrics and operational metrics makes it possible for future studies to optimize a supply chain network based on topological metrics, which are much faster to calculate. This provides prescriptive analytics for supply chain robustness, so that users can quickly evaluate many possible topological designs for large-scale supply chain networks.

The remainder of the paper flows as follows: Next, we introduce supply chain network topologies, their nature, attributes, and general constraints. This is followed by a description of the architecture of our robustness decision support system. The approach will generate a supply chain network based on a set of parameters including source, sink, and transshipment nodes as well as the number and strength of the edges connecting the nodes. After the network generator, we describe the scenario analyzer and disruption simulator where a disruption is introduced into the supply chain network, randomly or directed, based on decision maker preferences. In conjunction with the scenario analyzer and disruption simulator is the performance evaluator whose job is to provide metrics of the network. The performance evaluator provides topological metrics and optimized operational metrics. The topology analyzer of the performance evaluator will provide topological metrics such as largest connected component, characteristic path length the size of the largest functional sub-network, and average supply path length. The optimization solver in the performance evaluator considers the flow through the network by accounting for total units delivered and average delivery cost. An example application of the decision support system is presented to illustrate the efficacy of the approach. Results are presented for both random and targeted disruptions, and finally, we discuss implications and conclude.

2. Background

2.1.Supply chain disruptions

Supply chain disruptions are inevitable and they are varied. Disruptions are both natural and man-made, and they have been increasing in frequency and severity over the last decade [52]. Given the varied nature of disruptions and their unintended consequences [3, 43], as well as the fact that, unless contained, the disruptions will affect larger portions of the supply chain [3, 10, 33], it is critical to develop robust strategies to mitigate them.

2.2.Network science and robustness

The decision support method presented in this paper is grounded in network science which is defined as "the study of network representations of physical, biological, and social phenomena leading to predictive models of these phenomena" [13]. There is a considerable body of knowledge existing for network science in many domains such as transportation, telecommunications, biological, social, and supply chain, and while there is maturity in the field, there is also renewed and growing interest [29]. We do not present a comprehensive review of the literature, but we do draw from select domains and projects to support our research questions and direction. For example, researchers have used network science to draw insights into network disruptions in road networks for emergency services [40], telecommunication networks [23], spatial decision support systems and wireless communications [44, 45], and supply chain networks [12, 18, 31, 58].

Within the domain of network science, robustness has been studied in many fields such as finance [21], transportation [50], and group decision making [38]. Bruneau et al. [6] define robustness as the strength of a system, which is measured by its ability to resist damage or loss of functionality as a result of an event. Robustness is one component that contributes to a system's resilience [6, 65], specifically by fostering pre-event preparedness [66], and is particularly interesting in evaluating networks' ability to absorb disruptions [50]. In a supply chain context, robustness is the ability to maintain normal operations under different scenarios including the event of a disruption [5, 27, 28]. A supply chain network that is robust should compensate for disruptions with minimal impact in performance. One way to enhance the robustness of a supply chain network is to investigate its ability to maintain operations in the event of disruption by altering the structural level of the network. Therefore, in order to have a robust supply chain network, weak points or vulnerabilities in the system should be identified before the disruption occurs [5].

2.3.Supply network topology

Supply chain networks are dynamic, being made up of interacting entities with different roles, such as raw material suppliers, manufacturers, logistics, warehouses, retailers, customers, etc. Because supply chain networks involve collaboration of partners sharing real-time, and often incomplete information, some have argued that these networks are complex adaptive systems where they may change dynamically causing the networking problems to be ill structured and behavior based, thus making them difficult to be solved by analytical tools such as mathematical programming [36, 51]. Although entities vary in manifestation and application domains, we refer to them generically as network *nodes*. Topology and robustness have long been studied for their interplay in mitigating attacks and failures [1, 8, 17, 37, 51]. A topology shows how the *nodes* in a network are connected together by *edges* or *links*, in other words, the topology is the structure of the network. For example, in an (ER) random network model, new edges between nodes are added *randomly*. Many real-world networks (e.g. social networks and some supply chain networks) have scale-free topologies [2, 38], where the edges are added based on *preferential attachment*: high-degree nodes are more likely to be connected. Scale-free networks are very robust to random failures, but are fragile to targeted attacks [37]. Additionally, supply chain networks may exhibit small-world (commonly referred to as six-degrees of separation) characteristics where the nodes are locally well connected [15, 59]. Small-world networks share similar properties to random networks in regards to robustness to failures [37]. Thus, robustness will vary depending upon the model of topology.

Many previous topological robustness studies assumed that nodes in networks are *homogeneous* in the sense that the different roles of nodes are not considered. Yet, supply chain networks are essentially *heterogeneous* with different types of nodes with distinct roles, such as *supply nodes*, and *distribution (*or *transshipment) nodes*. As a result, when helping managers evaluate the robustness of various network topologies and redesign the supply chain network in cases of disruptions, we need to take node heterogeneity into consideration [63, 64]. In considering the topology of the supply chain network, we are mainly focusing on the logistic nature of the network, and note that supply chain networks are even more complex dealing with interpersonal, economic, and sourcing relationships. However, as per [3], the logistic nature of supply chains remains an area of importance.

It should be noted that supply chain networks are inclusive all the way from raw materials to finished goods and have many stakeholders and multiple tiers. In this research, we focus on the downstream components of a supply chain network related to the distribution of goods. In this part of a supply chain network, manufacturers, distributors and retailers are closely connected and supply chain managers often have high levels of knowledge and control over the network's structure. Given the nature of these supply chain networks, we limit the locus of control of topology to nodes. Prior research has investigated the effects of modifying links in the network to address disruptions (link-based or link-focused modeling) [40, 50] as well as node-based modeling [45, 61]. While supply chain managers are aware of links in their networks, such as road, rail, and air between the nodes, they are more often concerned with the health and well-being of the nodes in their networks such as suppliers, distribution centers, and warehouses [7, 9, 32, 54]. Even in supply chain network optimization problems, assumptions are often made that do not reflect the reality of actual supply chains. For example, there may not always be paths from source to sink nodes [35] due to transshipment node failures, or if a node fails in the supply chain, the network may not simply be rerouted around that node because that specific node is essential to adding value to the product or information traversing the chain. Therefore, we focus on node-centric modifications to improve or balance supply chain network robustness.

3. Architecture of a Decision Support Approach for Robustness Analysis

We adopt a framework for spatial decision support systems (SDSS) proposed by Snediker et al [48]. This framework, shown in Figure 1, aims at helping managers assess the robustness of supply chain networks with different topologies when exposed to disruptive events, so that they can make informed decisions about their network design. The main components of the system are the network generator, scenario analyzer, disruption simulator, performance evaluator and a network database. A user provides the network parameters and disruption scenarios (data input) to the scenario analyzer (impact assessment), which in turn invokes the network generator (scenario generation). The network generator creates a supply chain network based on the input provided, and stores it in a network database. The scenario analyzer also notifies the disruption simulator to simulate disruption scenarios according to users' requirements. The scenario analyzer passes the disrupted network to the performance evaluator (measurement comparison & testing), which can provide two types of performance metrics: one is derived only from network topologies and the roles of nodes; the other is based on the optimization of supply flows across the network. Lastly, the user may modify the supply chain network based on test results (impact exploration and disruption mediation).

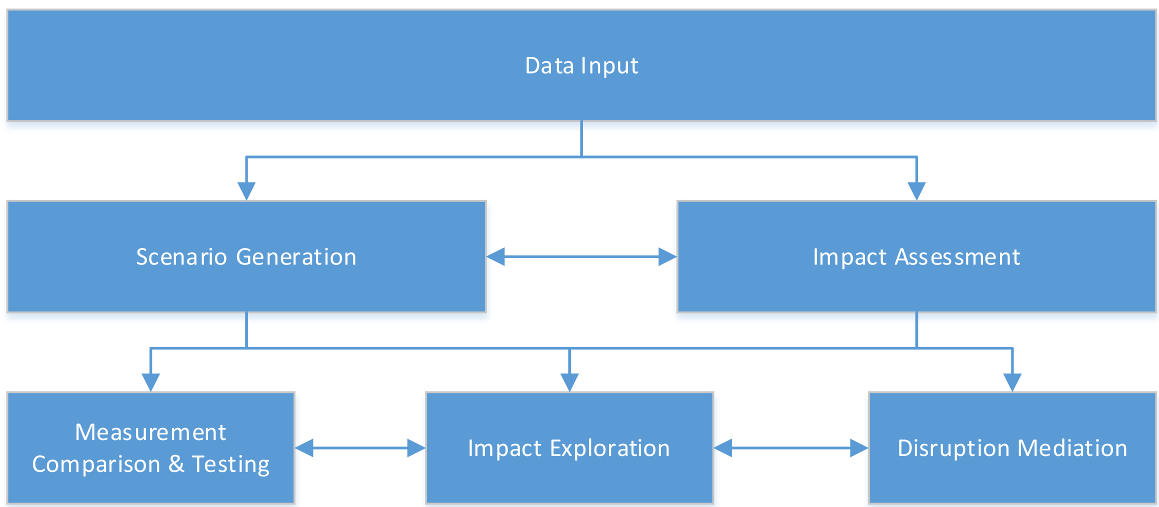


Figure 1. Snediker et al. [48] Framework for SDSS Network Scenarios

3.1. The network generator

Given a set of parameters, this component generates a supply chain network as specified by a user. The inputs include both topological parameters and attributes of individual elements in the network (as summarized in Table 1). We will use the simple supply chain network in Figure 2 as an example to illustrate the input parameters. The network has three types of nodes: *warehouses (W)*, *distribution centers (DC)* and *retail stores (S)*. Warehouses act as supply nodes, stores are demand nodes, and distribution centers are trans-shipment nodes. To build the network, one needs to specify the number of nodes for each type, the number of edges, and what is the network topology. In addition, each node is associated with two types of capacities: (1) the supply/demand (S-D) capacity denotes how many goods can be provided or consumed by a node. A supply node has a positive S-D capacity as it provides goods to the network; a demand node consumes goods provided through the network and has a negative S-D capacity; and a transshipment node has a zero S-D capacity; (2) the throughput capacity represents how many units of goods a node can transfer to other nodes. In other words, it is the capacity of a node to transfer goods it received from upstream suppliers to downstream customers. Users can specify the S-D and throughput capacities of a node on the basis of its type, designated role, location, etc. The capacity of a node may be increased at extra cost. Figure 2 illustrates an example of a supply chain network.

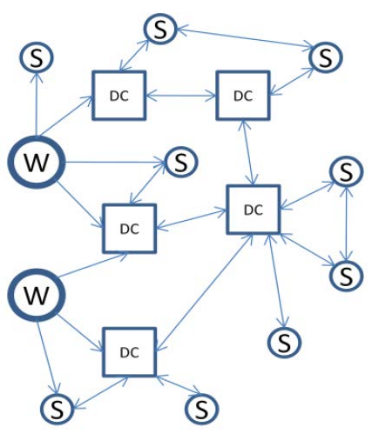


Figure 2. A simple supply chain network with 3 types of nodes: warehouses (W), distribution centers (DC) and stores (S).

As for edges, those between warehouses and DC/stores are uni-directional to denote the one-way flow of goods, while those between DCs and stores bi-directional. Edges are also assigned weights that represent the cost of transporting goods over a link in the physical world. The weight could depend on the geographical distance between two nodes, the means of transportation (by road, air, or sea), etc. Higher edge weight denotes higher transportation cost on the edge.

The network generator supports various strategies to construct networks with many different topologies. It also allows a user to modify the topology of an existing supply chain network through various adjustment strategies. It can generate networks with standard models, such as ER-random, scale-free, and small-world. More importantly, it also allows users to state specific requirements when constructing a supply chain network [59]. For example, the user can specify that each demand node connects to at least two distribution nodes, or that a supply node can handle no more than 10 distribution nodes. Further, the design of a supply chain network often faces some practical constraints. In some supply chain networks, a demand node may have to connect to a distribution node that is geographically more proximate than another distant distribution node. Thus, this generator also makes it possible to enforce an upper limit on the geographical distance that an edge can span in a supply chain network, so that the resulting network has fewer long-distance hops and reflects a more realistic supply chain. Table 1 summarizes the input and output parameters of our decision support system. It is worth noting that supporting network models listed in Table 1 are not comprehensive nor are real-world supply chains limited to those listed. For example, it is rare to find a supply chain network that is totally random. However, by allowing users to access these models, the system gives decision makers options for what-if analysis without being overwhelming. However, as described in our literature review, the models and parameters listed in Table 1 are most salient and pertinent for supply chain networks.

Table 1. Input and Output Parameters

Input	Nodes	Numbers of supply, distribution, and demand nodes	
		Supply/demand capacity	
		Throughput capacity	
		Geographical location (if available)	
	Edges	Number of edges	
		Directions of different types of edges	
		Weights of edges (if available)	
	Parameters related to network topologies	Scale-free	Degree preference exponent (*r*)
			The number of initial nodes
		ER-random	Connection probability
		Small world	Lattice pattern
			Rewiring probability
		Prioritized attachment for supply nodes	Numbers of edges each type of node can have
			Degree preference parameter
		Random Localized Rewiring	Parameters for the original network
			Rewiring probability
		Hierarchical	Numbers of edges each type of node can have
	Maximum connection distance	Geographical distance (kilometers or miles) or graphical distance (number of hops)	
	Disruption models	Elements to be disrupted	Node or/and edge
		Disruption type	Random, targeted (with the metric for importance), mixed, or user-defined.
		Number of elements to be disrupted	

Output	Supply chain network topology	Network adjacency matrix and the role of each node.
		Topological performance metrics (size of the largest functional sub-network and average supply path length).
	Supply chain network performance	Total units delivered (TUD)
		Average delivery cost (ADC)
		Flow of goods on each edge

3.2. The Scenario Analyzer and the Disruption Simulator

The *scenario analyzer* lies at the center of our architecture. It receives inputs such as supply chain network topologies and settings for simulating disruptions and other scenarios. The analyzer will invoke the disruption simulator to simulate disruptions to the supply chain network. The *disruption simulator* receives the disruption settings as input, such as the type of disruption (random/targeted/mixed/user-defined), the number of nodes/edges to be removed, and the strategy for selecting important targets, etc. Then it simulates these disruptions by removing nodes or edges from the network. *The output of the disruption simulator is the disrupted network.*

When disruptions are random, each node and/or edge has the same failure probability. These random disruptions might be accidental such as earthquakes, fires, or power outages. They may be unexpected economic events like the dot com bubble burst or a bankruptcy. In order to simulate these random disruptions, we randomly remove nodes or edges from the supply network. When a node is removed, the connected edges to that node are also removed. In contrast to random disruptions, targeted disruptions are directed at critical system entities such as network hubs. The criticality of a node may be measured by its importance in a network through measures such as *degree, closeness, and betweenness* [39]. In addition to *random* and *targeted* disruption scenarios, users may manually define how to remove nodes or edges from a supply chain network.

3.3. The Performance Evaluator

As its name suggests, the performance evaluator is responsible for evaluating the performance of a supply chain network after disruptions. It interacts with two other modules, each providing one set of performance metrics: the topology analyzer focuses on network topologies and generates topological metrics; the optimization solver formulates and solves an optimization problem to find operational metrics based on the optimal supply flows. We will illustrate how the two sets of performance metrics relate to each other in the case study later. After disruptions, the performance of a supply chain network usually deteriorates. The less its performance deteriorates, the more robust the supply chain network is. By comparing the values of a network's performance metrics before and after a disruption, the performance evaluator helps users gain insights into the network's robustness against disruptions.

3.4. The Topology Analyzer

Topological metrics have been used by many network studies to evaluate the robustness of a network [37]. The most important include the size of the largest connected component, clustering coefficient, and characteristic path length [37, 51]. The largest connected component of a network is the largest sub-network where there exists a path between any pair of nodes. The characteristic path length is the average shortest path length between all pairs of nodes. Clustering coefficient captures the nature of small-world networks in that the probability of the nearness of two nodes is related to the nearness of a third to the first two [37]. In the context of supply chain networks, topological metrics can also be good indicators of network performance [26].

Taking the topology of a supply chain network (weighted or un-weighted) and the role of each node in the network as inputs, this approach provides two topological metrics that extend the two aforementioned topological metrics [63, 64]. The first metric is *the size of the largest functional sub-network* (LFSN). A functional sub-network is also a connected component but it must have at least one supply node (e.g., a warehouse) in it. The larger the size of the LFSN is, the better the connectivity of the network is. The second metric is the *average supply path length* [63]. Instead of finding the path length between all node pairs as in characteristic path length, the average supply path length only considers shortest paths between all supply-demand nodes pairs, because these paths are more important for supply flows in a network. The smaller the value is; the easier supplies can be delivered from supply nodes to demand nodes. For example, in the supply chain network in Figure 3, the largest functional sub-network contains 4 nodes: W1, DC1, S1, and S2. The average supply path length is (2+1)/2=1.5 as only S1 and S2 can access a supply node (with shortest path length 2 and 1 respectively).

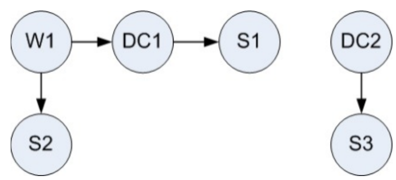


Figure 3. A sample supply chain network. (W for supply nodes, DC for distribution nodes, S for demand nodes, and directions of edges represent the flow of goods.)

Our topological metrics actually serve as a heuristic/approximation to operational metrics that can only be obtained after NP-hard optimization. The two topological metrics can be calculated in polynomial time. For example, finding the largest functional sub-network can be done through a breadth-first or depth-first search with a worst-case time complexity of $O(|E|+|V|)$, where $|E|$ is the number of edges and $|V|$ is the number of nodes in the network. Finding the characteristic path length has a worst-case time complexity of $O(|V|^3)$ when using the Floyd–Warshall algorithm [21], or $O(|E||V|+|V|^2\log|V|)$ when using the Dijkstra's algorithm [16]. Since a supply chain network often has many more demand nodes than supply nodes, the complexity for calculating the average supply path length can usually be further reduced.

3.5. The Optimization Solver

While topological metrics are easy to calculate, they only consider the network topology and omit many real-world constraints that supply chain networks usually face, such as capacities of a supply node and a distribution node. They are also based on concepts from graph theories and may be unintuitive to some supply chain network managers. Thus, the optimization solver provides *operational metrics* – another set of performance metrics based on the flow optimization in a supply chain network.

Total units delivered (TUD) is the total number of units of a good delivered from supply nodes to demand nodes in the network. It reflects whether demand nodes in the supply chain network can obtain their requisite supplies. It is not equal to the total supplies nor total demand. Only demand that is met by supplies through a supply chain network will count as TUD. A higher TUD means a superior performance. For example, in the supply chain network in Figure 3, stores S1 and S2 can access goods from warehouse W1, but S3 has no access to any warehouse. Thus, TUD is the number of goods transported from W1 to meet the total demand of S1 and S2.

In contrast to TUD, *Average Delivery Cost* (ADC) measures how much the delivery of one unit of goods costs. Clearly, a lower delivery cost indicates better performance of the supply chain network. In our experiment, we calculated TUD and AUC for all the whole network, even though it may be fragmented into isolated sub-networks after disruptions.

While there are often many ways to deliver goods through a supply chain network, finding the optimal one with the lowest total cost can be modeled as a capacitated transshipment problem [55], which can be solved using flow optimization techniques.

We formalize the flow optimization of a supply chain network as the following integer programming (IP) model (Table 1 summarized the key parameters in the model):

Model 1: Flow optimization of the supply chain network

Min $TotalCost = c(i,j)*f(i,j) + c_{add}(i)*add(i)$

Subject to (1) $\sum_j f(i,j) \leq sdc(i) + \sum_j f(j,i), \forall\, i$

(2) $\sum_j f(i,j) \leq tc(i) + add(i), \forall\, i$

(3) $f(i,j) = 0$, if node i and j are not direct neighbors in the network.

(4) $f(i,j)$ integer, $\forall\, i, j$

Where: i and j denote nodes in the network;

$f(i,j)$: flow on an edge or link from i to j

$c(i,j)$: the cost of transporting one unit of goods from node i to node j

$sdc(i)$: supply/demand capacity of node i

$tc(i)$: throughput capacity of node i

$add(i)$: the extra throughput capacity that node i adds

$c_{add}(i)$: the cost for node i to add one extra unit of goods to its throughput capacity

The objective function of the IP problem is the total cost of goods delivery for the supply chain network. $f(i,j)$ is the volume of goods transported from node i to j. Constraint 1 enforces the input-output flow balance at all nodes as the total output from node i cannot exceed the sum of node i's capacity $sdc(i)$ and the total input to i. Constraint 2 enforces the limit on throughput capacity of any node. The total flow through node i to other nodes cannot exceed its throughput capacity $tc(i)$. A node can also add extra throughput capacity $add(i)$, with the cost of $c_{add}(i)$ per unit of extra capacity. By allowing extra throughput capacity we can ensure that, as long as the total supply is greater than the total demand, and the network remains connected, there will be a feasible solution to the IP. Constraint 3 relates to the network structure: if nodes i and j are not direct neighbors in the supply chain network, they cannot forward any goods to each other directly. This formulation can be solved with a standard optimization package. Also, this model will have no feasible solution if the supply chain network or sub-network does not even have any supply node, as there will be no flow of supplies in such networks. It does not guarantee to meet the demand of every demand node either. In other words, after disruptions, even though a demand node is still somehow connected to a supply node, its demand may not be completely satisfied due to the loss of supply nodes. Similarly, a supply node may end up with excessive supplies that cannot be delivered to demand nodes.

It is worth noting that our work focuses on topological designs. Thus, the aforementioned IP model is about optimization at the strategic level. Similar to previous work on strategic-level optimizations, the IP model does not consider specific rules or constraints, such as sourcing, inventory management, transportation mode/carrier selections [49].

4. Implementation

The architecture has been implemented in a decision support system. Graph analysis and visualization are handled by the Java Universal Network/Graph Framework [41]. The optimization solver is based on GAMS. It takes input files, solves the IP problem, and returns the optimization results. In addition, the network generator also integrates a program that retrieves the geographical distance between two U.S. street addresses or zip codes. Distance retrieved by the program is used to assign the weight of edges, and to inform the topological design or rewiring of supply chain networks. Figure 4 shows a screenshot of the network graph as rendered by the system. It shows how warehouses (gray squares), distribution centers (white squares), and retail stores (white circles) are connected. An edge shows the direction (denoted with arrows) and the amount (with line width) of supply flows between two nodes. More information of nodes or edges will show in a pop-up menu when right-clicking them. In addition to the values of supply chain network performance metrics before and after simulated disruptions, Figure 4 only shows very basic information of the supply chain network being analyzed. It includes a snapshot of the network topology, node information, the direction and amount of supply flows.

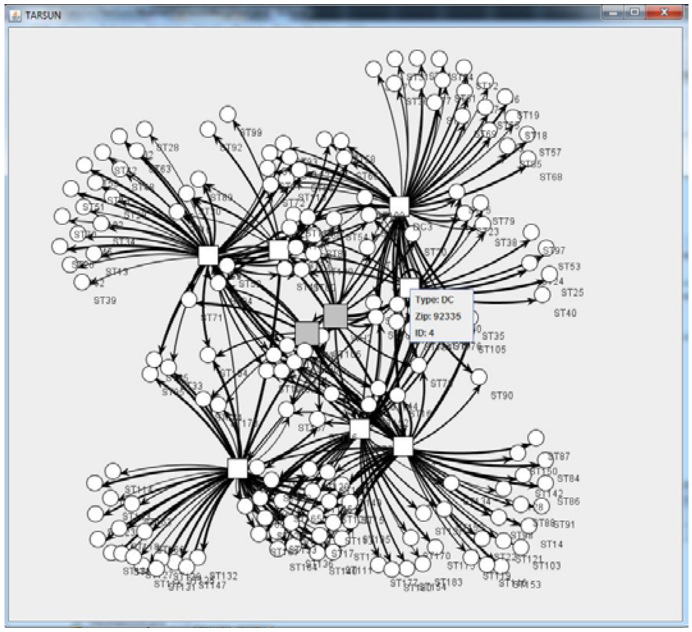


Figure 4. A screenshot of the network graph of the supply chain

The primary motivation to develop the decision support system as described is to demonstrate a reusable framework that may be adapted by decision makers to analyze networks that are varied in structure and complexity. Specifically, by modifying the network through a topological approach, decision makers can quickly evaluate the network robustness under various scenarios without determining the optimal solution for each scenario, similar to the strength of heuristics for quickly locating the global optimal solution region in complex non-linear optimization problems.

5. Example Application

5.1.Settings

To demonstrate the applicability of our approach, we use an example of a west coast, retailer distribution network to show how the system can help a firm's managers to evaluate the robustness of different supply chain network topologies against disruptions. The example application demonstrates how information provided by the system can help a decision maker evaluate the robustness of a real-world supply chain network against disruptions, and how adjustment to the network can change its robustness. However, although the example network has a degree distribution similar to those of scale-free networks, the goal is not to show a scale-free network's robustness against random or targeted disruptions. The network consists of 184 nodes: 2 warehouses, 7 distribution centers (DCs), and 175 stores. The edges of the network are directed and weighted. To make the case study more realistic, we do not allow the flow of goods from stores to warehouses, or from DCs to warehouses. The geographical distance (in miles) between two nodes will serve as the edge weight if they are connected. Table 2 lists key parameters for the example application of the retail supply chain network.

Table 2. Key parameters for the example application of a retail supply chain network.

Parameter	**Description**	**Parameter values for the case study**
sdc(i)	Supply/demand capacity of a warehouse, DC or Store	1000 for warehouse; 0 for DC; –10 for store
tc(i)	Throughput capacity of a warehouse, DC or Store	1000for Warehouse; 300 for DC; 100 for store
c(i,j)	Cost of transporting goods	$ 0.01 per mile per unit
$c_{ex}(i)$	Cost of using extra throughput capacity at any node	$ 0.10 per unit
d_{max}	Maximum rewiring distance	300 miles

Using the west coast retailer's supply chain network preferences, we simulate the following distribution network: First, two warehouses are interconnected. Second, distribution centers are randomly connected to either the first or second warehouse and to two other DCs. Third, each store is preferentially attached to a DC(s) within 300 miles. Lastly, 10% of all stores may connect directly to a warehouse. Figure 5 shows the degree distribution of the network. The network does not feature a perfect power-law degree distribution. Instead, it is a combination of two power-law degree distributions with some hierarchical features that lead to the polarization in node degrees. Stores that are lower in the hierarchy have degrees ranging from one to three and follow the power-law distribution (shown on the left in the figure). Alternatively, DCs and warehouses are generally higher in the hierarchy with degrees greater than 12. These warehouse and DC nodes also reflected in a power-law distribution (shown on the right in the figure). Although the network lacks nodes with degrees in between those of stores and DCs/warehouses, it still features a small number of hub nodes and many low-degree nodes, which is a key feature of scale-free networks. Figure 5 shows the complementary cumulative degree distribution of the west coast retailer's distribution network for our example application.

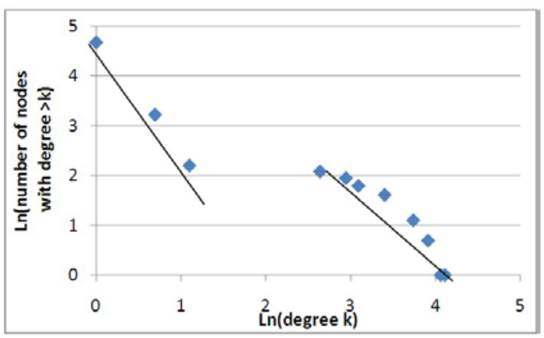


Figure 5. The complementary cumulative degree distribution of the retailer's distribution network

As an example of getting different topologies of the distribution network, we let the DSS adjust the topology of the network using random localized rewiring (RLR) [64]. It represents a preemptive strategy to adjust supply chain network structures to improve robustness against possible disruptions. Basically, RLR iterates through all edges in a supply chain network, disconnects an edge from one of its nodes with a rewiring probability p_r, and reconnects the empty end of the edge to another node within the rewiring radius d_{max}. A higher p_r value leads to more rewiring, while a lower d_{max} imposes more control over the rewiring process. RLR represents a heuristic strategy to adjust the topology of a supply chain network. The full rewiring algorithm was discussed in [64]. In the context of supply chain networks, rewiring represents the adjustment of supply delivery between entities in a supply chain network. For example, a retailer who used to receive goods from a DC switches to another nearby DC. In this case study, we used two different rewiring probabilities $p_r=0.25$ and $p_r=0.5$, and set rewiring radius $d_{max}=300$ miles.

To evaluate the robustness of the original and rewired distribution networks, we simulated random and targeted disruptions. Adhering to previous research [1], for targeted disruptions, node degree was used to indicate the importance of a potential target node, because node degree is simpler to determine. Because of their multiple connections, high-degree nodes often have high visibility [30]. Centrality measures (e.g. betweenness, closeness, and eigenvector centrality) are more difficult for attackers to obtain because they require greater knowledge of the network's topology. For both types of disruptions, we removed 3 DCs (out of 7), one at a time between each observation. After one DC is removed, the degree of each node is updated. For targeted disruptions, we removed the highest-degree DC left in the network. During the process of node removal, we tracked the two sets of performance metrics for the original and rewired networks. Figure 6 shows the logic of the simulation experiments. Figure 7 illustrates the networks' responses to *random* disruptions (with an average of 30 runs). Figure 8 shows the networks' responses to *targeted* disruptions (with an average of 30 runs).

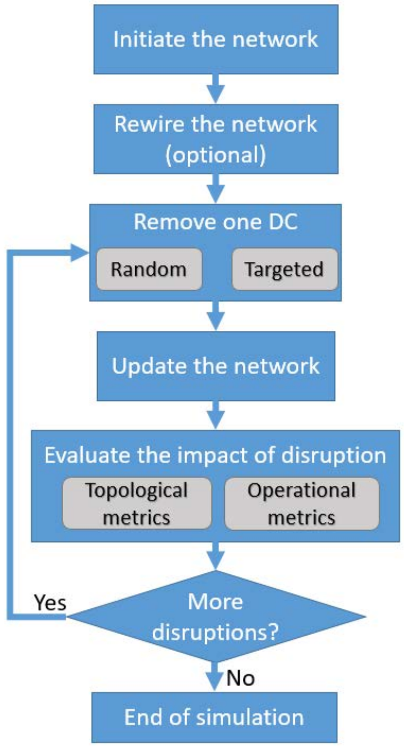
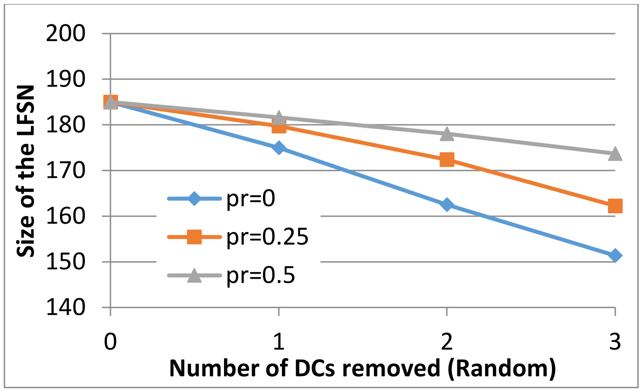
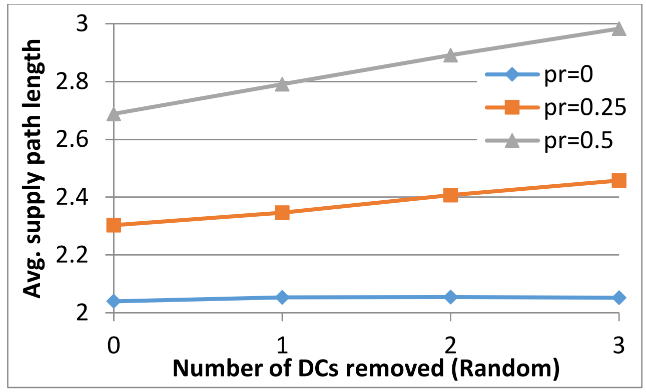


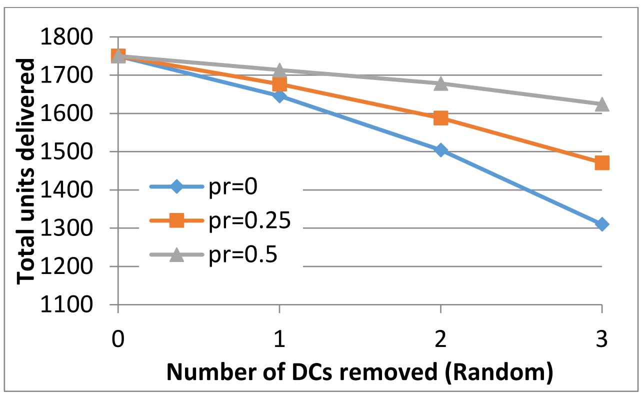
Figure 6. The flow chart of the simulation experiments.



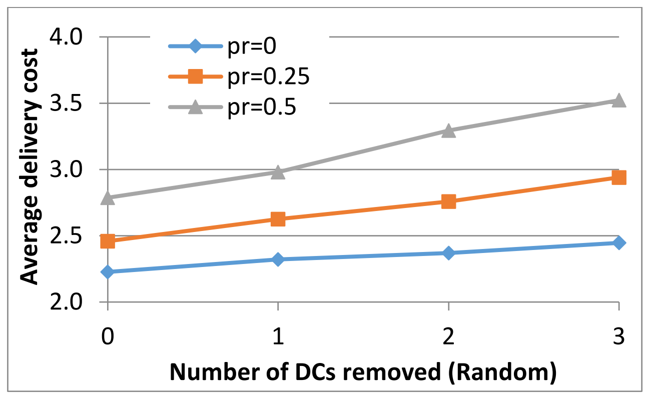
(a) Size of the largest functional sub-network (LFSN)



(b) Average supply path length

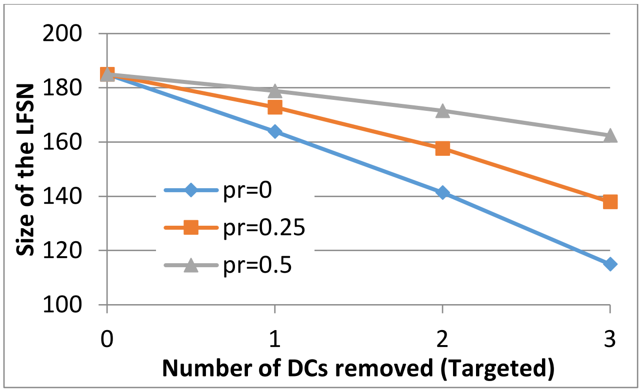


(c) Total units delivered (TUD)

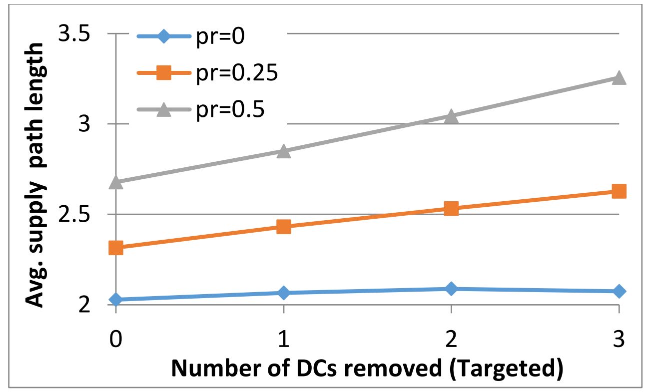


(d) Average delivery cost (ADC)

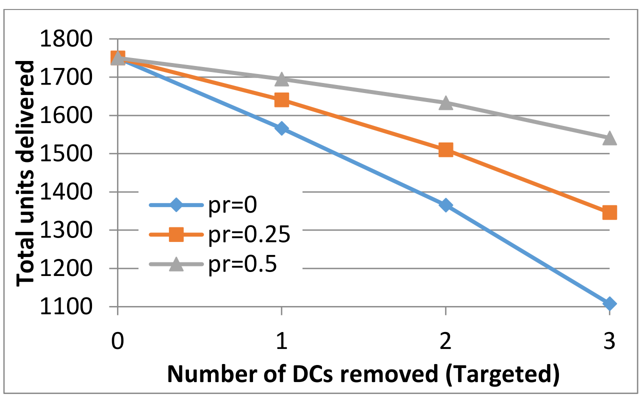
Figure 7. Various networks' responses to random disruptions



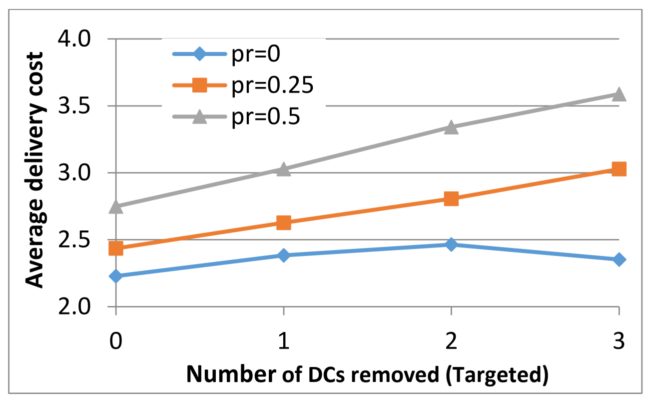
(a) Size of the largest functional sub-network (LFSN)



(b) Average supply path length



(a) Total units delivered (TUD)



(b) Average delivery cost (ADC)

Figure 8. Various networks' responses to targeted disruptions

5.2. Results

The performance of the original and the rewired distribution networks (with two different rewiring probabilities) under both random and targeted disruptions are shown in figures 7 and 8. The horizontal axis shows the number of removed DCs, and the vertical axis the performance metrics. For each disruption scenario, two sets of performance metrics (i.e., four metrics) are illustrated. For the original distribution network ($p_r=0$), its size of the LFSN and TUD deteriorate very fast, especially in targeted disruptions, because the network is easily fragmented by disruptions and many stores' access to warehouses is lost. Meanwhile, for those stores that can still access supplies, the network is able to maintain low average path length and ADC in both types of disruptions, because nodes in the network generally follow a hierarchical structure. Stores connect only to DCs or warehouses and not to each other. Therefore, if a store still has access to warehouses after disruptions, it means the closest warehouse is either an immediate neighbor or two hops away from the store. This is more obvious when 3 DCs are removed in targeted disruptions: the values of average supply path length and ADC actually decrease, because the possible long paths between supply and demand nodes have been eliminated after the removal of high-degree DCs.

Meanwhile, rewired networks perform better in terms of size of the LFSN and TUD. *With a higher p_r, the two metrics also have greater values.* For instance, in the rewired network with $p_r=0.5$, even after 3 important DCs fail, the distribution network only sees a drop of 6% in the size of the LFSN and a drop of 11% in TUD. As a trade-off, the average supply path length and delivery cost are higher than for the original network. This is because the distance between warehouses and stores is longer in this rewired network than in the more hierarchical original network. Note that the two rewiring probabilities are simply examples demonstrating the efficacy of the DSS. The choice of the two probabilities was to show the power of the topological component of the DSS compared to the traditional operational optimization and not to compare different distributions. Admittedly, rewiring a supply chain network may dramatically increase costs. Thus, as in any simulation, the closer to real world values and probability distributions a decision maker can get, the greater the accuracy our DSS can provide in evaluating supply chain robustness. See [63, 64] for comparative analyses of re-wiring given different levels of risk probabilities.

As Figures 7 and 8 suggest, comparing the robustness of these distribution networks using topological and operational metrics leads to similar conclusions. There is actually a high level of similarity between performance metrics provided by the topology analyzer and metrics from the optimization solver. In fact, as Table 3 shows, the trend in the size of the LFSN is very similar to that in TUD, and average supply path length resembles ADC. In other words, the topological metrics, which can be calculated in polynomial time, can closely approximate operational metrics, which are usually NP-hard optimizations. Thus, the topology analyzer can be used by managers to get a quick yet relatively accurate estimate of the robustness of a supply chain network. The existence of both the topology analyzer and the optimization solver is a desirable feature: the topology analyzer is handy when the manager needs to evaluate a very large supply chain network in a real-time fashion or compare a large number of possible topological designs of a supply chain network; the optimization solver is more appropriate when an in-depth analysis of a supply chain network's robustness is necessary.

5.3. Discussion

Such analysis can help a manager better understand this tradeoff in rewiring distribution networks. In the case of supply chain applications such as the example presented in this paper, re-wiring represents the adjustment of supply delivery between entities in a supply network. To find the appropriate topology for a distribution network, a manager has to balance performance metrics based on the firm's potential disruption scenarios, robustness requirements, and financial considerations. Consider the results in Figure 7, a manager faced with a prospect of two targeted disruptions might observe that when $p_r = 0.5$, TUD is 268 units more than if $p_r = 0$. Thus, assuming a profit of \$10 per unit, the profit increases by \$2,680. On the other hand, the delivery cost goes up by \$0.80 per unit for all the 1,633 units delivered, adding \$1,306 to the total cost. Hence, there is a net benefit of $1,374 to rewire the network with $p_r = 0.5$. Other disruption cases may be similarly evaluated. Table 3 summarizes the results of the example application, comparing the performance metrics of random and targeted disruptions on the original and rewired supply chain networks. It is worth noting that robustness can mean different things to different people and is very context dependent making it very hard to generalize. To one manager, it could mean maximizing units delivered at any cost, while to another it may mean attaining the highest rate of delivery subject to a maximum cost. In practice, it is mostly achieved, not in isolation, but by striking a balance between conflicting priorities usually through trial and error. Our interactive DSS tool makes this task easier for the manager to accomplish by allowing her to consider alternative scenarios quickly and easily, and then selecting the best topology that satisfies her constraints. Our contribution lies in developing a methodology for understanding robustness in supply chain networks and demonstrating how it can be applied in real world settings.

Table 3. Comparing the two sets of performance metrics.

Disruption scenarios	Distribution networks	Correlation coefficient (p-values)	
		Size of the LFSN vs TUD	Average supply path length vs ADC
Random disruptions	Original	0.9925 (0.0075)	0.9913 (0.0087)
	Rewired (P_r=0.25)	0.9993 (0.0007)	0.9944 (0.0056)
	Rewired (P_r=0.5)	0.9989 (0.0011)	0.9955 (0.0045)
Targeted disruptions	Original	0.9997 (0.0003)	0.9528 (0.0472)
	Rewired (P_r=0.25)	0.9999 (0.0001)	0.9969 (0.0031)
	Rewired (P_r=0.5)	0.9993 (0.0007)	0.9969 (0.0031)

6. Conclusions

Supply chain networks are highly vulnerable to disruptions [20]. Recognizing the importance of topology as one of the key determinants for supply chain robustness, we proposed a DSS to evaluate the robustness of different supply chain network topologies against disruptions. The architecture consists of a scenario analyzer, a network generator, a disruption simulator, and a performance evaluator. The network generator produces different topologies using various network building and adjustment strategies. The disruption simulator applies different types of random and targeted disruptions to a supply chain network. The robustness of a supply chain network against disruptions can be measured by two modules in the performance evaluator: (1) the optimization solver finds the optimal way to route goods through pre- and post-disruption supply chain networks by solving an optimization model based on an IP formulation. The optimization outcome provides key operational metrics such as *total units delivered, average delivery cost*, and *the flow of goods between nodes.* (2) The topology analyzer efficiently finds performance metrics through network topologies and the heterogeneous roles of nodes. The different roles of supply chain nodes are modeled to represent real world supply chains. Thus, the DSS's ability to provide the two sets of performance metrics further improves its power in evaluating different topological designs of supply chain networks, and those networks' abilities to perform at a desired level in the presence of disruptions.

It is desirable to have both topology analyzer and the optimization solver within a decision support tool like the one we proposed for two reasons: First, it offers two different use cases for managers to evaluate the performance of their distribution networks against disruptions. The topology analyzer useful when a manager needs to evaluate the post-disruption performance of a large distribution network in real time or to compare the post-disruption performance of a large number of possible topological designs of a supply distribution network. The optimization solver is more appropriate if an in-depth analysis of a supply distribution network's robustness is necessary. This is because computing topological metrics from the topology analyzer (polynomial time) is much faster than finding an optimal solution from the optimization solver (NP-hard). Using the topology analyzer also makes it possible for managers to use this tool beyond their own distribution network, because it is easier to collect data for an inter-form supply chain network's topology than operational data at different firms (e.g., delivery cost and capacities of other firms). With topology analyzer metrics, a manager can get an estimation of how the firm's supply chain network would perform if a disruption occurs.

We demonstrated the efficacy of our decision support system through an example application of a retailer's distribution network. Managers can perform scenario analysis and use this DSS to evaluate how different topologies affect the robustness of a supply chain network. Decision makers can perform stress tests of their supply chains through "what if" analyses by building and modifying supply chain networks [9, 11]. By doing so, decision makers should be able to ask questions like "what is the effect on our network when this node goes down?" or "what happens when an unexpected (random) disruption occurs?" These stress tests compare the performance of supply chain networks under multiple topologies and disruption events, which will enable decision makers to increase the network robustness. Although a firm does not often build a supply chain network from scratch, they do make frequent adjustments to respond to today's dynamic global markets [34] and launch new initiatives in rebuilding their supply chain networks [19]. Thus, our DSS also allows a manager to adjust the topology of an existing supply chain network in many ways and analyze the effect of doing so.

In addition, this approach also enables managers to study how varying other parameters in a supply chain network will influence its robustness. Managers often underestimate or simply ignore the potential impact of disruptions in their supply chains. This DSS offers an interactive visualization, measurement, and optimization of the influence of disruptions and their mitigation through topological design. For instance, a user may specify a range of values or statistical distributions for supply/demand capacities, throughput capacities, as well as transportation and distribution costs. The performance evaluator can generate different weighted networks and optimization models for these parameter values and evaluate the different "what-if" scenarios corresponding to them. Also, by analyzing the removal of which nodes/edges produces the most impact, a manager can identify the most critical entities that should be fortified or protected. This decision support system fills a research gap in robustness and supply chain network design [9, 11].

A limitation of this research is the lack of automation in selecting the ideal topology. However, this limitation is partly due to the ontology of supply chain networks. While it would be ideal to allow the DSS to select the optimal network, very often network nodes and edges are selected for reasons that fall outside of linear parameters. For example, a specific supplier may or may not be selected based on some past experience or organizational knowledge. Organizations have been burned by single source suppliers, and create policies such as never to have less than two sources. It may also be that there is a strong personal relationship that exists between the decision makers of a supplier-customer business relationship that affects the topology of the network in spite of the inherent risks. Thus, we believe that a DSS as an aid for decision makers is the most appropriate approach to this complex problem. Instead of deriving the optimal topology based on the mathematical programming components of the DSS, we choose to provide a set of alternatives and let the decision maker perform what-if analysis with the DSS. The complex nature of human decision making with subtle and often non-explicit constraints is what continues to drive the need for decision support systems over completely automated decision systems. Another limitation of this research is the focus on node-centric models. Supply chain networks may also suffer from disruptions in the links between nodes, such as rail strike, highway closure, air delay or closure due to weather or strike. Thus, supply chain managers would benefit by not only evaluating node failures, but also specifically link failures. There has been research in this area, specifically in the transportation domain [40, 50], and supply chain networks would benefit from these models as well. Finally, this research is limited to the context of transshipment and logistics, and thus is not generalizable to all networks.

For future research, we would like to add additional constraints to the IP model in the optimization solver such as upper limits on the capacities of nodes or flows along edges to observe their effect on supply chain network performance and robustness. It would also be interesting to investigate supply chain network robustness via a link-based approach as well as measuring the assortativity of the network [15]. Additionally, as robustness is one component for resiliency, we envision an enhanced decision support system that would measure a supply chain network's ability to recover to pre-disruption performance levels as well as the rate of recovery [62]. Lastly, real-time event management would allow decision makers the ability to quickly respond to disruptions, and thereby reduce the impact of the disruptions.

References

[1] R. Albert, H. Jeong, A.-L. Barabási, Error and attack tolerance of complex networks, Nature, 406 (2000) 378-382.

[2] A.L. Barabasi, R. Albert, Emergence of scaling in random networks, Science, 286 (1999) 509-512.

[3] J.V. Blackhurst, C.W. Craighead, D. Elkins, R.B. Handfield, An empirically derived agenda of critical research issues for managing supply-chain disruptions, International Journal of Production Research, 43 (2005) 4067-4081.

[4] J.V. Blackhurst, K.P. Scheibe, D.J. Johnson, Supplier risk assessment and monitoring for the automotive industry, International Journal of Physical Distribution & Logistics Management, 38 (2008) 143-165.

[5] E. Brandon-Jones, B. Squire, C.W. Autry, K.J. Petersen, A Contingent Resource-Based Perspective of Supply Chain Resilience and Robustness, Journal of Supply Chain Management, 50 (2014) 55-73.

[6] M. Bruneau, S.E. Chang, R.T. Eguchi, G.C. Lee, T.D. O'Rourke, A.M. Reinhorn, M. Shinozuka, K. Tierney, W.A. Wallace, D. von Winterfeldt, A framework to quantitatively assess and enhance the seismic resilience of communities, Earthquake Spectra, 19 (2003) 733-752.

[7] P. Burnson, Procurement is Top Area of Risk, Consero Survey Reveals, Supply Chain Management Review, Peerless Media LLC, 2015.

[8] D.S. Callaway, M.E. Newman, S.H. Strogatz, D.J. Watts, Network robustness and fragility: Percolation on random graphs, Physical Review Letters, 85 (2000) 5468.

[9] S. Chopra, M.S. Sodhi, Managing risk to avoid supply-chain breakdown, MIT Sloan Management Review 46 (2004) 53.

[10] S. Chopra, M.S. Sodhi, Supply-chain breakdown, MIT Sloan Management Review, 46 (2004) 53-61.

[11] S. Chopra, M.S. Sodhi, Reducing the Risk of Supply Chain Disruptions, MIT Sloan Management Review, 55 (2014) 73-80.

[12] M. Christopher, H. Peck, Building the resilient supply chain, International Journal of Logistics Management, 15 (2004) 1-14.

[13] N.R. Council, Network Science, The National Academies Press, Washington, DC, 2005.

[14] C.W. Craighead, J. Blackhurst, M.J. Rungtusanatham, R.B. Handfield, The severity of supply chain disruptions: design characteristics and mitigation capabilities, Decision Sciences, 38 (2007) 131-156.

[15] S. Derrible, C. Kennedy, The complexity and robustness of metro networks, Physica A: Statistical Mechanics and its Applications, 389 (2010) 3678-3691.

[16] E. Dijkstra, A note on two problems in connexion with graphs, Numerische Mathematik, 1 (1959) 269-271.

[17] S.N. Dorogovtsev, J.F. Mendes, Evolution of networks, Advances in Physics, 51 (2002) 1079-1187.

[18] M.N. Faisal, D. Banwet, R. Shankar, Quantification of risk mitigation environment of supply chains using graph theory and matrix methods, European Journal of Industrial Engineering, 1 (2007) 22-39.

[19] E.D. Fassoula, Transforming the supply chain, Journal of Manufacturing Technology Management, 17 (2006) 848 - 860.

[20] J. Fiksel, M. Polyviou, K.L. Croxton, T.J. Pettit, From risk to resilience: learning to deal with disruption, MIT Sloan Management Review 56 (2015) 79.
[21] R.W. Floyd, Algorithm 97: Shortest path, Communications of the ACM, 5 (1962) 345.
[22] A. Ghadge, S. Dani, R. Kalawsky, Systems thinking for modeling risk propagation in supply networks, 2011 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), IEEE, 2011, pp. 1685-1689.
[23] T.H. Grubesic, A.T. Murray, Vital nodes, interconnected infrastructures, and the geographies of network survivability, Annals of the Association of American Geographers, 96 (2006) 64-83.
[24] E.J. Hearnshaw, M.M. Wilson, A complex network approach to supply chain network theory, International Journal of Operations & Production Management, 33 (2013) 442-469.
[25] U. Jüttner, S. Maklan, Supply chain resilience in the global financial crisis: an empirical study, Supply Chain Management: An International Journal, 16 (2011) 246-259.
[26] Y. Kim, T.Y. Choi, T. Yan, K. Dooley, Structural investigation of supply networks: A social network analysis approach, Journal of Operations Management, 29 (2011) 194-211.
[27] W. Klibi, A. Martel, The design of robust value-creating supply chain networks, OR Spectrum, 35 (2013) 867-903.
[28] W. Klibi, A. Martel, A. Guitouni, The design of robust value-creating supply chain networks: a critical review, European Journal of Operational Research, 203 (2010) 283-293.
[29] L. Kocarev, V. In, Network science: A new paradigm shift, IEEE Network: The Magazine of Global Internetworking, 24 (2010) 6-9.
[30] V. Latora, M. Marchiori, Vulnerability and protection of infrastructure networks, Physical Review E, 71 (2005) 4.
[31] S. Lazzarini, F. Chaddad, M. Cook, Integrating supply chain and network analyses: the study of netchains, Journal on Chain and Network Science, 1 (2001) 7-22.
[32] I. Manuj, J.T. Mentzer, Global supply chain risk management strategies, International Journal of Physical Distribution & Logistics Management, 38 (2008) 192-223.
[33] K.A. Marley, P.T. Ward, J.A. Hill, Mitigating supply chain disruptions–a normal accident perspective, Supply Chain Management: An International Journal, 19 (2014) 142-152.
[34] R. Martin, Changing the Mind of the Corporation, Harvard Business Review (1993) 81-94.
[35] A. Nagurney, Optimal supply chain network design and redesign at minimal total cost and with demand satisfaction, International Journal of Production Economics, 128 (2010) 200-208.
[36] A. Nair, R. Narasimhan, T.Y. Choi, Supply Networks as a Complex Adaptive System: Toward Simulation-Based Theory Building on Evolutionary Decision Making, Decision Sciences, 40 (2009) 783-815.
[37] A. Nair, J.M. Vidal, Supply network topology and robustness against disruptions–an investigation using multi-agent model, International Journal of Production Research, 49 (2011) 1391-1404.
[38] M.E.J. Newman, The structure and function of complex networks, SIAM Review, 45 (2003) 167-256.
[39] M.E.J. Newman, Mathematics of networks, in: L.E. Blume, S.N. Durlauf (Eds.) The New Palgrave Encyclopedia of Economics, Palgrave Macmillan, Basingstoke, UK, 2008.
[40] D.C. Novak, J.L. Sullivan, A link-focused methodology for evaluating accessibility to emergency services, Decision Support Systems, 57 (2014) 309-319.

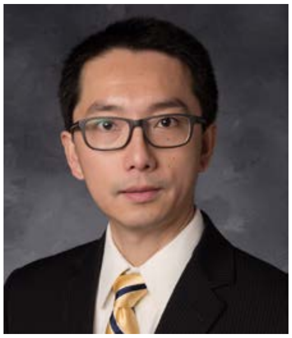
[41] J. O'Madadhain, D. Fisher, T. Nelson, S. White, Y.-B. Boey, The Java Universal Network/Graph Framework (JUNG): A Brief Tour, Music-to-Knowledge North American Workshop, University of Illinois, 2005.
[42] J.B. Rice, F. Caniato, Building a Secure and Resilient Supply Network, Supply Chain Management Review, 7 (2003) 22-30.
[43] K.P. Scheibe and J.V. Blackhurst, Supply Chain Disruption Propagation: A Systemic Risk and Normal Accident Theory Perspective, Internation Journal of Production Research, In Press (2017).
[44] K.P. Scheibe, L.W. Carstensen, T.R. Rakes, L.P. Rees, Going the last mile: a spatial decision support system for wireless broadband communications, Decision Support Systems, 42 (2006) 557-570.
[45] K.P. Scheibe, C.T. Ragsdale, A model for the capacitated, hop-constrained, per-packet wireless mesh network design problem, European Journal of Operational Research, 197 (2009) 773-784.
[46] B. Shi, A Decentralized Mechanism for Improving the Functional Robustness of Distribution Networks, IEEE Transactions on Systems, Man, and Cybernetics, Part B, OnlineFirst (2012) 1-14.
[47] J.B. Skipper, J.B. Hanna, Minimizing supply chain disruption risk through enhanced flexibility, International Journal of Physical Distribution & Logistics Management, 39 (2009) 404-427.
[48] D.E. Snediker, A.T. Murray, T.C. Matisziw, Decision support for network disruption mitigation, Decision Support Systems, 44 (2008) 954-969.
[49] Spinnaker, Introduction to Strategic Supply Chain Network Design, Spinnaker Management Group LLC, www.spinnakermgmt.com 2012.
[50] J. Sullivan, D. Novak, L. Aultman-Hall, D.M. Scott, Identifying critical road segments and measuring system-wide robustness in transportation networks with isolating links: a link-based capacity-reduction approach, Transportation Research Part A: Policy and Practice, 44 (2010) 323-336.
[51] A. Surana, S. Kumara*, M. Greaves, U.N. Raghavan, Supply-chain networks: a complex adaptive systems perspective, International Journal of Production Research, 43 (2005) 4235-4265.
[52] C.S. Tang, Robust strategies for mitigating supply chain disruptions, International Journal of Logistics: Research and Applications, 9 (2006) 33-45.
[53] H.P. Thadakamalla, U.N. Raghavan, S. Kumara, R. Albert, Survivability of Multiagent-Based Supply Networks: A Topological Perspective, IEEE Intelligent Systems, 19 (2004) 24-31.
[54] G.S. Van Der Vegt, P. Essens, M. Wahlström, G. George, Managing risk and resilience, Academy of Management Journal, 58 (2015) 971-980.
[55] H.M. Wagner, On a Class of Capacitated Transportation Problems, Management Science, 5 (1959) 304-318.
[56] S.M. Wagner, C. Bode, An empirical investigation into supply chain vulnerability, Journal of Purchasing and Supply Management, 12 (2006) 301-312.
[57] S.M. Wagner, C. Bode, Dominant risks and risk management practices in supply chains, Supply Chain Risk, Springer (2009), pp. 271-290.
[58] S.M. Wagner, N. Neshat, Assessing the vulnerability of supply chains using graph theory, International Journal of Production Economics, 126 (2010) 121-129.

[59] D.J. Watts, S.H. Strogatz, Collective dynamics of ‘small-world’networks, Nature, 393 (1998) 440-442.
[60] A. Wieland, C. Marcus Wallenburg, Dealing with supply chain risks: Linking risk management practices and strategies to performance, International Journal of Physical Distribution & Logistics Management, 42 (2012) 887-905.
[61] F. Xie, D. Levinson, Measuring the structure of road networks, Geographical Analysis, 39 (2007) 336-356.
[62] X. Zhang, E. Miller-Hooks, K. Denny, Assessing the role of network topology in transportation network resilience, Journal of Transport Geography, 46 (2015) 35-45.
[63] K. Zhao, A. Kumar, T.P. Harrison, J. Yen, Analyzing the resilience of complex supply network topologies against random and targeted disruptions, IEEE Systems Journal, 5 (2011) 28-39.
[64] K. Zhao, A. Kumar, J. Yen, Achieving high robustness in supply distribution networks by rewiring, IEEE Transactions on Engineering Management, 58 (2011) 347-362.
[65] C.W. Zobel, Representing perceived tradeoffs in defining disaster resilience, Decision Support Systems, 50 (2011) 394-403.
[66] C.W. Zobel, L. Khansa, Characterizing multi-event disaster resilience, Computers & Operations Research, 42 (2014) 83-94.

Appendix: Pseudo-code for the RLR rewiring algorithm adapted from (Zhao, Kumar and Yen 2011).

```
Given a supply chain network G(V, E) ;
Given a rewiring probability p_r and a rewiring radius d_max.
foreach (edge e_i ∈ E){
        rnd = Random(0,1); // Generate a random number
        If (rnd < p_r) {
                v_i^(1) = endpoint 1 of edge e_i  (v_i^(1) ∈ V);
                v_i^(2) = endpoint 2 of edge e_i  ( v_i^(2) ∈ V);
                If degree(v_i^(1)) > degree(v_i^(2))
                        Rewire(e_i, v_i^(2));
                else if  degree(v_i^(2)) > degree(v_i^(1))
                        Rewire(e_i, v_i^(1));
                else if degree(v_i^(2)) == degree(v_i^(1))
                        Rewire(e_i, v_i^(2)) or Rewire(e_i, v_i^(1)).
        }
}
Function Rewire (e_rewire, v_toKeep){
        E = E − {e_rewire}.
        Identify V_r⊂V, such that ∀v_j ∈V_r, 0<distance(v_toKeep,v_j)≤ d_max;
        v_new =Random(v_j ∈V_r);
        If (v_new ≠ v_toKeep, and v_new ∉ direct neighbors of v_toKeep ){
                e_rewire= Connect(v_toKeep, v_new);
                E = E + {e_rewire}.
        }
}
```

Author Bios



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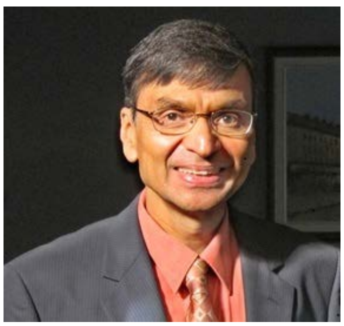

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